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Flexible investment under uncertainty in smart distribution networks with demand side response: Assessment framework and practical implementation

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HIGHLIGHTS

- A real options framework for distribution network investments under uncertainty.
- Smart (flexible) and asset-based investment values are compared transparently in Microsoft Excel.
- Both economic and physical (interruption) risks are measured in a multi-criterion analysis.
- Case study shows the value of demand response for deferring asset-based investments.
- Probabilistic regulatory frameworks are thus needed to give flexible investments their fair value.

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ABSTRACT

Classical deterministic models applied to investment valuation in distribution networks may not be adequate for a range of real-world decision-making scenarios as they effectively ignore the uncertainty found in the most important variables driving network planning (e.g., load growth). As greater uncertainty is expected from growing distributed energy resources in distribution networks, there is an increasing risk of investing in too much or too little network capacity and hence causing the stranding and inefficient use of network assets; these costs are then passed on to the end-user. An alternative emerging solution in the context of smart grid development is to release untapped network capacity through Demand-Side Response (DSR). However, to date there is no approach able to quantify the value of 'smart' DSR solutions against 'conventional' asset-heavy investments. On these premises, this paper presents a general real options framework and a novel probabilistic tool for the economic assessment of DSR for smart distribution network planning under uncertainty, which allows the modeling and comparison of multiple investment strategies, including DSR and capacity reinforcements, based on different cost and risk metrics.

In particular the model provides an explicit quantification of the economic value of DSR against alternative investment strategies. Through sensitivity analysis it is able to indicate the maximum price payable for DSR service such that DSR remains economically optimal against these alternatives. The proposed model thus provides Regulators with clear insights for overseeing DSR contractual arrangements. Further it highlights that differences exist in the economic perspective of the regulated DNO business and of customers. Our proposed model is therefore capable of highlighting instances where a particular investment strategy is favorable to the DNO but not to its customers, or vice-versa, and thus aspects of the regulatory framework which may need altering.

The case study results indicate that DSR can be an economical option to delay or even avoid large irreversible capacity investments, thus reducing overall costs for networks and end customers. However, in order for the value and benefits of DSR to be acknowledged, a change in the regulatory framework

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(currently based on deterministic analysis) that takes explicit account of uncertainty in planning, as suggested by our work, is required.

1. Introduction

Demand-side resource planning is a key priority for distribution network operators (DNOs) as Section 9 of HMSO, 1989 (the Electricity Act 1989, as amended in HMSO, 2000) places an obligation on DNOs to develop and maintain an efficient, coordinated and economical system of electricity distribution and to facilitate competition in the supply and generation of electricity. Subject to a combination of tight controls and incentives from the UK Regulator, Ofgem, DNOs must comply with very high standards regarding the security of electricity supply, customer service and customer safety, while guaranteeing the least possible cost to the consumer. These objectives have traditionally been achieved through network planning that seeks minimum cost network investment schemes satisfying the power transfer requirements from generation to loads while considering N-1 security and ensuring compliance with the Engineering Recommendation P2/6. These generally include high-voltage network or primary substation reinforcements such as the expansion and replacement of new overhead lines, underground cables, switchgear and power transformers in heavily loaded substations, while maintaining and repairing current network components. However, not only are these solutions extremely costly, but given today's highly uncertain outlook for peak demand trends, they simply may not be required or prove cost-effective in the longer term. An alternative, or complement, to traditional solutions is the application of smart innovative schemes, including DSR, Active Network Management (ANM), storage and the connection of Distributed Generation (DG) (Onen et al., 2014; Poudineh and Jamasb, 2014; Shaw et al., 2010) directly to the network. However, a rigorous framework for quantifying the benefits of these alternatives that takes into account uncertainty in future peak demand growth as well as managerial response to new information as it arrives over time is still lacking.

1.1. Contribution

The main contribution of this work is the design of a novel real options (RO) framework and the development of a relevant tool that can provide DNOs with a means of making long-term investment decisions in demand-side resource planning in smart distribution networks under a coherent and easily interpretable probabilistic framework. The RO approach to valuing flexible investments under uncertainty is combined with the simplicity and practicality of an Excel-based spreadsheet tool so that the framework can readily be implemented into the existing planning or policy-development processes of DNOs or Regulators. The benefits of this framework include:

1) Determining the optimal long-term investment strategy under currently available information.
2) Ranking the considered strategies by the *expected cost* metric – this in particular answers the open and important question as to the value of non-asset based solutions such as DSR relative to “classical” asset based solutions such as network reinforcement.
3) The use of expertly chosen scenarios, with probabilistic analyses within each scenario, in addition to overall analysis.
4) An approach to determining the breakeven pricing level in a DSR investment strategy so as to quantify the maximum payment price for contracting DSR customers, thus allowing appropriate regulation of DSR contractual arrangements.
5) Quantification of the economic and physical risks associated with specific strategies, to address relevant techno-economic requirements set out by the Regulator.

The policy implications of our proposed RO framework include highlighting the economic value of DSR as a potentially cost effective alternative to traditional capacity investment, with benefits eventually passed on to the end customers, and more direct involvement in system operation of more network users, namely DSR providers. However, for these benefits to become material and DSR to be effectively deployed, a regulatory change is needed that allows explicit consideration of uncertainty in planning, as opposed to the deterministic analysis that is currently required. The DSR payment price calculated by our model can also help the Regulator oversee contractual arrangements defined by the DNO. Finally, our quantitative model is able to highlight differences that may exist between the economic perspective of the regulated DNO business and of customers in general. When a strategy is favorable to the DNO but not to its customers in general, regulatory oversight of investment projects is needed to ensure that such a strategy is not followed. Conversely when a strategy is favorable to customers but would financially penalize the DNO business, this highlights situations in which the regulatory framework may need to be altered. Finally, when both DNO and customer perspectives lead to the same choice of strategy, this suggests that what is good for the DNO business is also good for its customers.

1.2. Paper structure

This paper is organized as follows. Section 2 presents the gaps in the current regulatory framework that require attention in order to systematically assess and compare different investment strategies under a coherent framework that takes into account the relevant uncertainties. Section 3 describes our multi-layered methodology for modeling uncertainty, separating long-term and shorter-term uncertainties in a way that is consistent with real-world planning and decision-making. Different metrics for selecting optimal strategies are also defined. Section 4 describes a case study and data for two different investment strategies, which are then compared in Section 5 using our Excel-based RO tool using different cost and risk metrics. Finally, conclusions and potential policy implications from these results are discussed in Section 6.

2. Regulatory framework

2.1. Current framework

Ofgem's (2013) RIIO network regulation model (Revenue = Incentives + Innovation + Outputs) aims at regulating DNOs, improving network reliability, providing environmental benefits and reducing costs while delivering the required ‘network outputs’ through a set of schemes that promote innovation (Ofgem, 2015). Within this context, a Cost Benefit Analysis (CBA) framework was developed as part of the Price Review to allow DNOs to assess the attractiveness of their proposed investment solutions and negotiate with Ofgem appropriate cost allowances allowing them to recoup their costs, while protecting the interests of electricity end-users. It allows the comparison of solutions based on consistent and comparable cost metrics associated with the different investment plans (Martínez Ceseña et al., 2016). Nonetheless, the CBA approach proposed for RIIO-ED1 (Ofgem, 2013) relies on a deterministic framework, namely the discounted cash flow (DCF) method of Net Present Value (NPV). It uses a single scenario for demand evolution, implicitly assuming that future demand growth is deterministic and certain for the entire lifetime of the project, which neglects the fact that DNOs have to make investment decisions based on uncertain best view forecasts. The CBA approach thus consistently eliminates any other possible scenario from the analysis and fails to properly reflect both real-world uncertainty and the flexibility of management to respond to such uncertainties once actual outcomes are known (Avner and Strange, 1996). Indeed, given that distribution network investments are planned over long time-scales (several decades) and that there are multiple and significant sources of uncertainty, particularly in demand evolution, energy prices and weather conditions that affect the required level of network capacity, an appropriate evaluation framework should consider uncertainty in its analysis. Furthermore, the dissemination of low carbon distributed technologies both on the demand side (e.g., electric heat pumps and electric vehicles) and on the supply side (e.g., wind, solar and cogeneration) will cause projections of net electricity demand, and therefore of the level of required capacity, to be even more uncertain (Department of Energy and Climate Change (DECC), 2014; Schachter and Mancarella, 2015). In this context the flexibility offered by distributed energy solutions such as DSR or DG could help defer or even avoid costly irreversible network upgrades (Martínez Ceseña and Mancarella, 2016; Strbac, 2008; Yang et al., 2008), thus potentially reducing capital costs.

2.2. Framework for flexible investment valuation methods

The need to incorporate uncertainty in network investment planning was in fact already recognized by Ofgem in their consultation document in (Ofgem, 2012) (although there has not been any follow up to this in the regulation of electricity distribution). Similar preliminary studies were carried out by the New Zealand Regulator in (Boyle et al., 2006). Both reports suggest a more flexible tool based on the theory of financial option pricing for assessing the desirability of potential investments in gas and electrical transmission network capacity, respectively. Nonetheless, in their modeling of uncertainty in future gas demand for gas networks (Ofgem, 2012), Ofgem makes strong assumptions, assuming peak demand to follow a geometric brownian motion (GBM). Indeed in economic applications, standard and geometric Brownian motion (or Wiener processes), as well as mean-reverting processes, have extensively been used in the literature, for example to model electricity and gas prices (Buzarquis et al., 2011; Cheng et al., 2011; Davis and Owens, 2003; Fuss et al., 2008; Marreco and Carpio, 2006). Yet, for RO applications, there is no guarantee that the model of a physical variable such as peak demand in a network should follow any of these standard stochastic processes such as GBM (Schachter and Mancarella, 2016).

These approaches however stress the need for providing a means of a) modeling uncertainty and b) modeling the managerial response to new information as it arrives over time. In this respect, applying option pricing models to value real assets, in other words taking a RO approach, as described in (Schachter and Mancarella, 2016), enables decision makers to model active decision making as uncertainty gives way to information. It accounts for the fact that, in reality, decision makers will seek to take advantage of future better conditions when they occur and, conversely, will seek to minimize the impact of future poorer conditions should they arise. RO therefore does not create additional flexibility, but highlights in a quantitative way the value of the flexibility that is available in decision making, which is particularly important in a network investment context. Since flexibility adds value, investments giving management the ability to respond appropriately in a variety of future scenarios have the potential for higher RO value. RO thinking hence does not favor projects that are more flexible but simply highlights the benefits from flexibility that other techniques such as those based solely on deterministic DCF analysis cannot. The result is that RO analysis allows a reasonable comparison between flexible and inflexible network investment strategies by giving both their fair value. Nonetheless, current RO methods are typically either too simplistic to be of use in investment planning for distribution networks, or alternatively overly computationally complex for practical implementation.

2.3. Electricity North West Ltd. Capacity to Customers solution

Distribution networks in Great Britain are designed according to Engineering Recommendation P2/6 with a suitable amount of spare emergency capacity, which is seldom used as emergency conditions may arise only once every three years or less frequently (Electricity Northwest Limited, 2013). Electricity North West Limited, one of the DNOs in the UK, has proposed a new DSR solution that involves contracting larger non-domestic customers to provide post-fault demand response in order to release spare capacity during normal operations that would otherwise be used only under emergency conditions. The project, named Capacity to Customers (C_2C) (Electricity North West Ltd., 2014), attempts to reduce network investment costs by automating the network, reconfiguring it and using DSR to release untapped capacity during emergency conditions. Essentially, the network, when healthy, is normally operated beyond the capacity suggested by the security standards; then, if a fault occurs and the network is thereby subject to overloading, a suitable amount of contracted DSR is activated and load is disconnected (see (Syrri et al., 2015) for more details). As a result, thermal and voltage problems can be more efficiently managed with DSR deployment allowing demand to grow beyond security limits (e.g. based on P2/6 engineering limits (Martínez Ceseña and Mancarella, 2014)). The C_2C method, currently under trial in the UK, could hence be an attractive alternative (or complement) to costly medium-voltage (MV) network or primary substation reinforcements, while also potentially achieving important benefits for customers (Martínez Ceseña et al., 2015). DNOs must adapt to cope with these changes as underinvestment could potentially lead to greater customer interruptions and incentive penalties on the DNO, while overinvestment could cause the underutilization and stranding of certain assets, which would also lead to large financial penalties for the DNO if Ofgem declares these investments inefficient (Shaw et al., 2010). Assessing and mitigating this risk is therefore important and having flexible investment plans that can easily be altered in the event that the future develops differently from expected can prove extremely valuable. The profitability of these more flexible alternatives, including a more efficient utilization of current network assets and investments in smart technologies, must therefore be assessed on a fair basis alongside traditional network upgrades.

3. Proposed methodology

3.1. Uncertainty modeling – a multi-layered approach

In this work, particular emphasis is placed on the fact that uncertainties are of different kinds. Long-term peak demand uncertainty is modeled using a small number of scenarios, to which is then added a complementary approach, a random process of smaller magnitude to capture short-term variations around the long-term trend, thus taking account that such scenarios are merely representative. In total, this provides a transparent approach to the simulation of future peak demand as it evolves over time, allowing real-time management responses to also be simulated in a transparent and consistent way. In addition to providing quantitative results, our use of simulation and modeling of management responses therefore provides a 'playable model' from which decision makers can gain a better understanding of the potential benefits of, for example, DSR as an alternative to reinforcement, which can be used to inform policy makers and regulators on the best investment strategies and appropriate specification of DSR contracts.

3.1.1. Layer 1: strategies

The layered approach proposed aims at combining the best available RO techniques in the most appropriate way. Layer 1 represents different investment strategies corresponding to a predefined set of interventions that take place at "tipping points" over the lifetime of the analysis, as each simulation progresses. The tipping points may be deterministic, such as the planned installation of an asset in say 2019; alternatively they may depend on the simulation itself, such as the use of DSR if and when peak demand reaches a certain trigger level. Each set of independent simulations will therefore typically have different tipping points reached at different times, and this feature is both realistic and helps illustrate the spread of risk and outcomes. In the developed tool, each investment strategy is composed of a set of up to three interventions (though the model is not limited by the number of interventions and could be expanded as needed) that can include the implementation of traditional network reinforcements (small or large) and DSR interventions.

As examples, a single-intervention strategy could be to make a conventional reinforcement when peak demand rises to an appropriate tipping point. A two-intervention strategy could be to begin using a certain level of DSR when a first tipping point is reached, and then to make a conventional reinforcement if and when peak demand achieves a second, higher tipping point. While these strategies are very sound, there is potential to include other strategies to be purposely devised through expert consideration, such as increasing DSR in stages over a series of progressively higher tipping points. In fact, by increasing the considered flexibility, these further strategies could provide insight into the optimal staging of investment decisions. In any case, the interventions and their associated costs and implementation lead times should be accurately represented in the strategies considered and so expert engineering input into the techno-economic assessment is highly valuable. We hence assume that when the number of potential strategies is large, expert judgment is first used to determine which strategies are likely to be competitive and this smaller screened set is then entered into the RO model.[1]

[1] In extreme cases when the number of strategies to be analyzed is very large, an optimization model may be applied in addition to the RO model, either embedded within the RO analysis engine or whose results need to be provided exogenously to the RO engine; for an example of such an optimization see (Martinez Cesena and Mancarella, 2016).

3.1.2. Layer 2: scenarios

Standard industry practice is to model long-term peak demand uncertainty using a small number of scenarios (Layer 2) chosen by a combination of modeling, stakeholder input and expert judgment (e.g., National Grid's Future Energy Scenarios (National Grid, 2014)); we model the underlying trend in future peak demand in this way. A manageable number of scenarios are first constructed for the most important uncertain variable driving network investment, namely *peak demand growth*. In this way, the decision maker clearly and directly specifies long-term uncertainty, possibly taking advantage of existing 'in-house' scenario analyses. Each of these scenarios is then given a probability weight, representing the expert's view on the likelihood of that scenario materializing (relative to the other representative scenarios). The most straightforward approach to selecting these probability weights is to choose scenarios that are perceived to be equally likely as futures. However, this approach may not allow a sufficiently diverse set of scenarios to be explored, such as best and worst cases. A central scenario may then be up-weighted and extreme scenarios may be down-weighted, while all other scenarios remain equally probable (this is the approach taken by Electricity North West). However, this is not strictly necessary and any combination of probability weights may be used, provided that they sum to 100%.

3.1.3. Layer 3: Monte Carlo simulations

While uncertainty over peak demand growth is represented principally by the choice of scenarios in layer 2, a level of "noise" (Layer 3) may be generated around the otherwise smooth trajectories in each scenario. This takes appropriate account of short-term uncertainty in factors such as weather and in the precise trajectory of peak demand growth, as well as to add both realism and a better representation of the spread of risk, recognizing the fact that each peak demand scenario, although chosen by an expert, is itself uncertain. They can also model variations in economic activity and customer behavior including addition/removal of demand from a large customer on the network. We therefore add Monte Carlo simulation of short-term variations by running a number of independent simulations per scenario (500 in our case study), which are independently repeated for each strategy in order to properly represent the spread of risk. The increase or decrease in the materialized noise over each year is modeled using a normal distribution with mean 0 and appropriate standard deviation, being the single parameter to be chosen by the decision maker. However, this uncertainty is not restricted to a normal distribution and any appropriate distribution can be applied provided that the spreadsheet software can simulate it. While less fundamental than long-term trends, these smaller fluctuations can nevertheless have material consequences in the context of demand-side interventions, as the fluctuation may be material to the scale of the added capacity from DSR. Indeed, not taking account of such fluctuations can lead to the underestimation of risk, both financial and physical, varying in degree for different kinds of interventions. If the scenarios for peak demand used in Layer 2 are "weather corrected" (in the sense that they do not take account of potential adverse weather conditions), then short-term variations due to weather may also be modeled in this way in the proposed tool. Additionally, variations in DSR performance may also be modeled, which may for instance be lower than expected, either because of an insufficient number of contracted customers or because not enough DSR load is online for disconnection when needed. Similarly, we may lack knowledge over contract price expectations from DSR customers. All of these smaller scale uncertainties can also be simulated, but are not limited to, using a standard normal distribution with an appropriate mean and standard deviation. The noise term, which models the aggregate

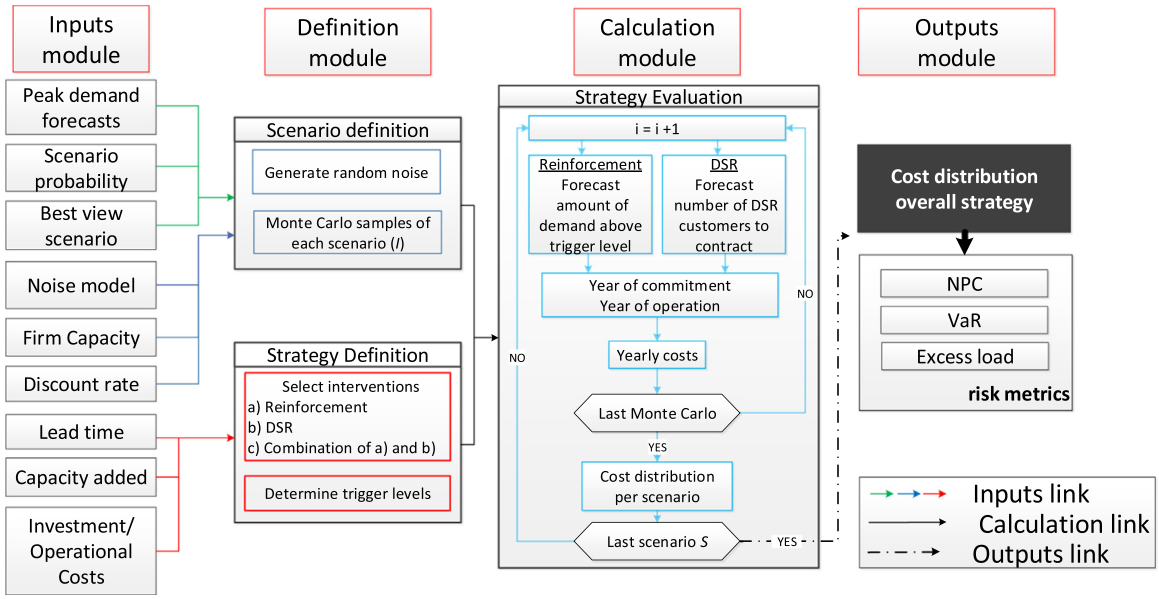

Fig. 1. Methodology flowchart.

effect on peak load of all such small scale uncertainties, is simulated repeatedly and independently for each strategy and in each scenario, and in each case the required physical and financial risk metrics are calculated across these sets of independent simulations.

3.2. *Tipping points and decision rules*

The tipping points, which are used to define flexible investment strategies, are expressed as simple decision rules. These decision rules should reflect the realistic and rational actions of the decision maker. A particularly important consideration is that the decision rules should only use the information that is available *at the time of the decision itself*. While this of course means that the subsequent stranding of assets cannot in general be ruled out, it is the only realistic approach to modeling decision making (indeed, any RO model which permits decisions to be taken on the basis of *future* information will give artificially high values to flexible investments). This point is well illustrated by the issue of construction lead times, which are typically significant for all interventions and in particular for traditional reinforcement. Because of these lead times, the year of commitment to a particular intervention should take into account the anticipated rate of growth in peak demand, aiming to finish construction or implementation before peak demand grows excessively. In order to avoid using future information not known at the time of commitment, a method for *projecting* demand forward must be specified. In our tool this is achieved by specifying a “best-view” scenario for demand growth, representing the trajectory of future demand that the expert considers to be the most likely future to occur. The best view forecasts are applied on a rolling basis by adding the corresponding yearly change in peak demand under the best view scenario to each available scenario of demand growth. In this way, investment decisions can be simulated in a realistic manner by considering the imperfect information provided by the best view forecasts.

These decision rules, including lead times and best view projections as appropriate, are then applied year after year, looking along each simulated demand path in turn. In this way, for each Monte Carlo simulation (for each strategy and in each scenario) the year in which each intervention is made (up to three in each defined strategy) is determined.

3.3. *Cost and risk metrics*

Once the timing of each intervention has been determined by application of the above decision rules, both the financial cost of interventions and the trajectory of the network's capacity are known. For each strategy, the distribution of costs and physical risk may then be calculated across the set of Monte Carlo simulations, from which key metrics may be calculated. Examples of such metrics are.

1) Financial indicators such as the average net present cost (NPC).
2) Physical risk indices such as the number of times peak load might not be met or the amount per year of excess peak load over capacity.
3) Other decision theoretic metrics such as least worst regret (Carpaneto et al., 2011a, 2011b).

A flowchart illustrating the entire methodology is presented in Fig. 1.

4. Data – case study description

To illustrate how the model works, we first examine a simple investment decision using three scenarios for peak demand growth (illustrated in Table 1) and comparing two different investment strategies. For illustrative purposes we will first use the data in Section 4.1 to perform a standard scenario analysis, determining the cost of two different investment strategies under each scenario. In Section 4.2 we will then proceed to apply our proposed RO spreadsheet tool to the comparison of the two alternative investment strategies.

In this case study, the abovementioned standard deviation is set equal to 0.06 MVA, being 0.5% of the initial peak demand level (15.45 MVA), following discussion with the network operator. Other numerical assumptions include a 4.5% discount rate as required in the Regulator's CBA (different discount rates may also be applied to the same case study in order to provide other financial perspectives). We assume that relevant forecasts of peak demand

Table 1
Peak demand scenarios.

Years	0	1	2	3	4	5	6	7	8	9	10
S1	15.45	15.88	16.09	16.12	16.27	16.63	16.68	16.84	17.03	17.23	17.40
S2	15.45	15.61	15.71	15.79	15.95	16.10	16.36	16.44	16.61	16.80	17.01
S3	15.45	15.50	15.57	15.60	15.69	15.86	16.05	16.10	15.92	15.73	15.70

Fig. 2. Cost breakdown for reinforce (R) strategy.

are available until 2026, thus considering a timeframe of 10 years.[2] The network in question consists of a 33 kV primary substation with two 11.5/23 MVA transformers supplied on a 33 kV radial network, feeding approximately 10,000 customers, and has a firm capacity of 16 MVA. If peak demand grows as predicted in scenario S2 (solid yellow/light-color line), the network's firm capacity limit will be reached in year 5 and continue growing beyond this until the end of the period of analysis (year 10).

The two investment strategies to be considered are:

1) Reinforce strategy (R strategy): in a location where the distribution network is constrained, consider increasing firm capacity at the substation by overlaying and replacing 4.5 km of 33 kV circuits, allowing the full capacity of the transformer to be utilized, at a cost of £1200k with a two-year construction and installation lead time. This investment would add a large capacity of 1.50 MVA to the network and the total cost of £1200k would be divided over the two-year lead time as shown in Fig. 2. The description of this intervention, as required for the proposed Excel spreadsheet tool, is given in Table 2. Strategy R has no future flexibility, as opposed to adding smaller capacity with the flexibility to expand later, if needed. Despite having a typically higher total capital cost, the latter variation on this asset-based strategy would retain some timing flexibility as the investment would then be made in two stages: in particular, it could be more economical than strategy R if peak demand begins to decline before the initially added capacity is exceeded. However for brevity we choose the 'one-shot' strategy R in this case study to represent network reinforcement; for consistency the same approach to reinforcement is also taken in the next strategy described below.
2) DSR then Reinforce-if-necessary strategy (DSR-R strategy): alternatively, DSR is deployed in the same location before adding any line and/or transformer by upgrading and automating the network to enable C_2C operation at a cost of £20k with a one-year lead-time for installation and a future payment of £20k/MVA/year for availability of DSR (and no additional payment for utilization in the event of a fault). If peak demand continues to grow beyond the capacity added by this DSR intervention, then the substation reinforcement described in Table 2 would also subsequently be made, but if this tipping point is not reached then the substation reinforcement could be entirely avoided. Table 3 shows inputs for the DSR intervention required in our spreadsheet tool (the inputs for the reinforcement intervention are the same as in Table 2).

[2] In order to account for longer timeframes, such as the end of RIIO-ED2 in 2031 or the 45-year time horizon suggested by Ofgem, residual values may be included in the model to take account of residual asset values in 2031.

Table 2
R strategy inputs.

Input name	Numerical value
Lead time (from year committed to year delivered)	2 years
Capacity added from intervention	1.50 MVA
Main investment cost	£1200k
Spread of costs (£k)–year committed	£0
Spread of costs (£k)–year+1	£204k
Spread of costs (£k)–year+2	£996k

Table 3
DSR-R strategy inputs.

Input name	Numerical value
Lead time (from year commitment to year delivered)	1 year
Maximum DSR customer availability	0.90 MVA
Average size of DSR customer contract	0.30 MVA
Initial DSR network automation costs	£20k
DSR contract set-up cost	£8k per customer
DSR customer automation	£25k per customer
DSR payment to contracted customer	£20k per MVA per year
Ongoing costs (remittances, automation maintenance and contract management)	£1.25k
Minimum DSR contract period	3 years

5. Results and discussion

5.1. Standard scenario analysis

In this section, we will perform the simplest possible analysis, in which the optimal sequence of interventions is determined for each of the three scenarios. This analysis is by nature 'ex post' and reveals the best possible interventions. While this provides useful information, it is of course unrealistic as it does not reflect the fact that interventions are made only on the basis of the information available at the time of the decision itself, as discussed in Section 2.2 above.

Under scenario S2, the least-cost strategy would be the R strategy: commit to reinforcement in year 3 and reinforce the network by adding an extra 1.50 MVA capacity at year 5, accounting for the 2-year lead time, as shown in Fig. 3. Based on a discount rate of 4.5% as in Ofgem's pre-tax Weighted Average Cost of Capital (WACC) (Ofgem, 2013), this strategy leads to a NPC of £970k. The alternative DSR-R strategy of delaying the investment

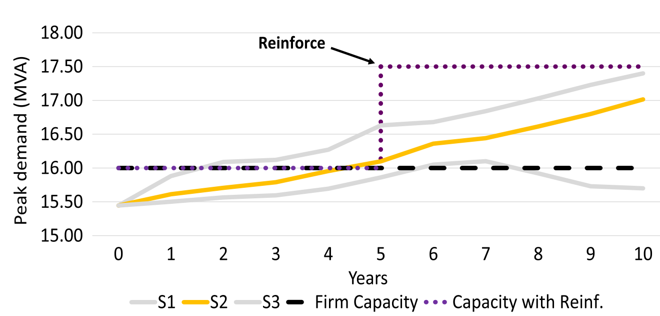

Fig. 3. Investment under scenario S2 (best view) for R strategy.

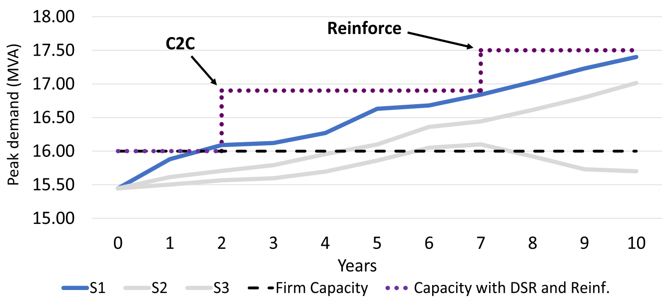

Fig. 4. Investment under scenario S1 (high load) for DSR-R strategy. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

by utilizing DSR and adding a (non-physical) capacity of 0.9 MVA before reinforcing, leads to a NPC of £979k, of which £50k comes from DSR and £929k from reinforcement. Since the requirement for additional capacity in the final year is greater than the maximum amount of DSR available (0.9 MVA), a reinforcement is inevitable. However, if DSR availability were set to 1.50 MVA then DSR alone would suffice; the NPC would then be £194k and reinforcement would thus be avoided. The maximum limit on DSR customer availability is therefore a crucial assumption in the assessment.

However, if demand grows faster than anticipated and scenario S1 occurs (solid dark-blue/dark-color line in Fig. 4) then the substation reinforcement would need to be installed much earlier, by year 2. Because of the effect of financial discounting, this leads to an increased NPC of £1107k. In this case, the alternative DSR-R strategy adding a (non-physical) capacity of 0.9 MVA, could potentially delay the investment by 2 years, as DSR can be used from year 2 until year 7, thus allowing time for the substation reinforcement to be installed in year 7. Due to financial discounting this strategy would in fact lead to a lower NPC of £1040k. In this case, the C_2C intervention can be considered an economically attractive means to defer costly traditional investments, as illustrated graphically in Fig. 5. Finally, if demand initially grows more slowly than anticipated and indeed subsequently falls, as in the case in scenario S3 (dashed blue/light-color line), then the C_2C intervention can be used to avoid the substation reinforcement entirely (over the 10-year timeframe of this analysis). In this case, the DSR-R strategy proves to be financially much more attractive, since there is effectively no stranding of assets and the NPC is £63k compared with an NPC of £928.5k for strategy R.

5.2. Extending scenarios via Monte Carlo simulation

We now demonstrate the effect of adding Monte Carlo simulations to the simple scenarios above, as discussed in Section 3.1.3. Fig. 6 illustrates the effect of adding noise terms around Scenario S2 with a standard deviation of 0.5% in each year. In particular, we

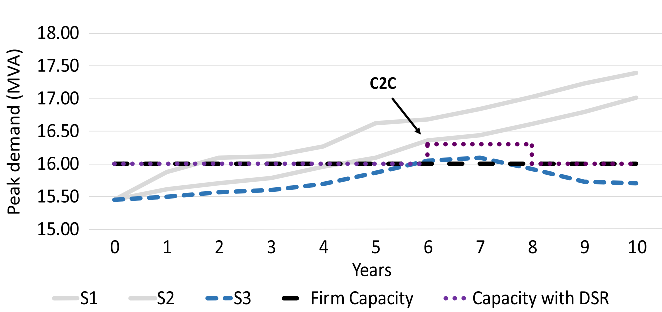

Fig. 5. Investment under scenario S3 (low load growth) for DSR-R strategy. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

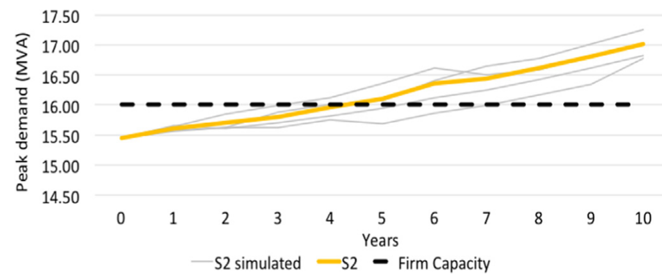

Fig. 6. Uncertainty around scenario S2.

see that each simulated path now passes the 16 MVA capacity limit at a different time, thus extending the range of the three scenarios defined in Table 2 and providing a more realistic spread of potential outcomes.

5.2.1. Financial cost metrics

For each of the Monte Carlo simulations illustrated in Fig. 6 above (layer 3), for each scenario (layer 2) and within each strategy (layer 1), the decision rules may now be applied and the financial cost and spread of physical risk evaluated as described in Section 2.2. The financial cost is evaluated by discounting to obtain the NPC in each Monte Carlo simulation, and the physical risk is evaluated by recording the instances of excess load and their extent year by year. In the spreadsheet tool, this information is then summarized across simulations in the form of graphical empirical cost and excess load distributions. Fig. 7 below provides an illustration for the DSR-R strategy showing the empirical distribution of the NPC in each of the three scenarios. As can be seen, under scenario S1 (dark-blue/dark color), all Monte Carlo runs give NPC values above £900k since all the DSR is used as much as possible to defer capacity investments but is still not sufficient to substitute for load growth in future years; hence a capacity reinforcement is also needed. The NPC therefore combines DSR costs with reinforcement costs in later years. For scenario S2, on the other hand, DSR can, for some Monte Carlo runs, suffice to satisfy the required demand levels in all years; hence, the only costs incurred are from investing in DSR. This is seen by the distribution on the left-hand side (in yellow/light color, behind S3), where the costs do not exceed £180k. However, for other Monte Carlo runs, a reinforcement strategy, without any DSR, is needed; this is displayed by the yellow distribution on the right-hand side, where costs are between £840k and £1020k. Finally, for scenario S3 (light blue), in almost all Monte Carlo runs DSR is enough to satisfy the demand, hence most costs are below £220k, yet, for some Monte Carlo runs, a reinforcement is needed (seen from the infrequent costs between £900k and £960k). These cost distributions can therefore quickly provide a decision maker with a graphical interpretation of the costs involved with a DSR-R strategy when considering each distinct scenario.

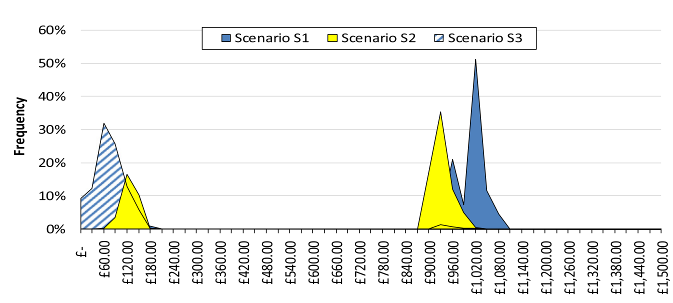

Fig. 7. Scenario-specific net present cost for DSR-R strategy. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

Table 4
Scenario weights chosen by expert input.

Scenario	Weight (%)	Volatility (%)
Scenario S1 (high load)	20.00	0.50
Scenario S2 (best view)	60.00	0.50
Scenario S3 (low load)	20.00	0.50

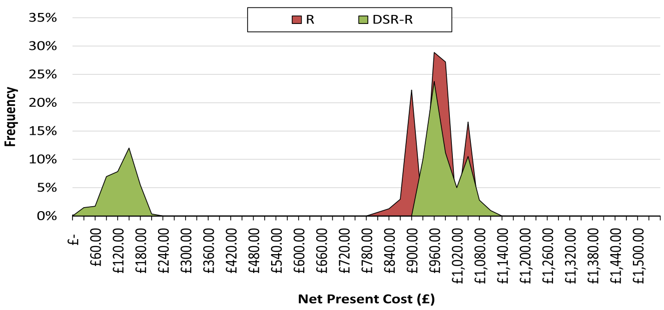

Fig. 8. Overall weighted net present cost distributions for strategies R and DSR-R. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

5.2.2. Analysis across scenarios and optimal strategy selection

The empirical scenario-specific histograms illustrated in Fig. 7 may now be combined, given a set of scenario probability weights chosen by expert input, as illustrated in Table 4 (this is mathematically consistent, and corresponds to applying the Law of Total Probability). This overall weighted empirical distribution is illustrated for both strategies in Fig. 8, where the green/light-color distribution represents the NPC for the DSR-R strategy and in red/dark-color for the R strategy.

For each considered strategy, the overall average cost and financial risk metrics (see Section 2.3) may be calculated from this overall cost distribution, as in Table 5. Selection of the optimal strategy will typically be by lowest overall average cost, subject to the preferred strategy having financial risk metrics at an acceptable level. It should be noted, however, that the availability of overall cost distributions in our tool enables a wide range of possible metrics, and these metrics may be applied as the user prefers in order to select the optimal strategy.

5.2.3. Physical risk metrics

The issue of physical risk is also significant in this study since using lower capacity interventions such as DSR while waiting for more information exposes the network to the risk of a rapid increase in demand, which might not be quickly addressed due to lengthy construction times. As described in Section 5.2, this excess demand in the network is recorded in each Monte Carlo simulation. From this information, empirical distributions may again be calculated as described in Section 5.2.1 (per scenario) and Section 5.2.2 (overall). Thus the physical risk associated with excess demand may be analyzed in just the same way as financial metrics. This feature allows each investment strategy to be assessed jointly in terms of both its financial cost and physical network reliability. Fig. 9 provides a useful graphical illustration of this reliability information using boxplots.

Table 5
Results.

Metric	Cost of R strategy (£k)	Cost of DSR-R strategy (£k)
Average NPC	981	647
Standard deviation of NPC	41	299

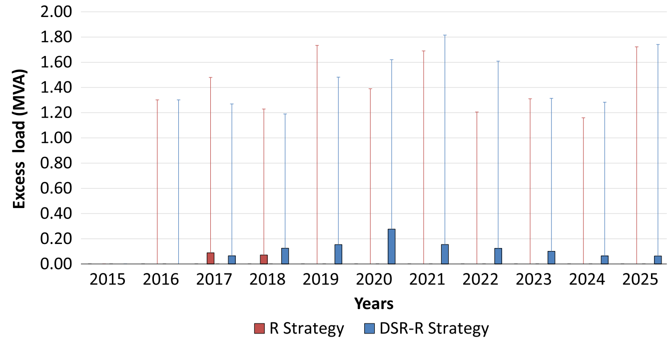

Fig. 9. Boxplot of excess load per year. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

Since different interventions provide different amounts of capacity, the boxplots provide a visual comparison between strategies of the level of reliability achieved by each strategy. In Fig. 9, the red and blue boxes, for the R and DSR-R strategy respectively, represent the initial (lower) 75% of the distribution, while the upper whiskers represent the remaining 25% of the distribution, in other words the higher, more extreme cases. For instance, in year 2016, 75% of all Monte Carlo runs for the R Strategy (red) give an excess load of 0 MVA, since no box is present, while at most 25% of them have an excess load between 0 and 1.3 MVA. Similarly, in year 2017, 75% of the distribution, in other words 75% of all Monte Carlo runs, gives an excess load between 0 and 0.10 MVA, while the most extreme 25% give an excess load between 0.10 and 1.50 MVA. From Fig. 9, it is clear that the lower average cost of the DSR-R strategy (blue) is balanced by a correspondingly higher physical risk profile compared with the traditional reinforcement R (red). While there is no more than a 25% likelihood of exceeding capacity (excess > 0 MVA) in all years except for 2017 and 2018 under the R strategy, since at least 75% of the distribution is 0 (there are no boxes apart from in 2017 and 2018), there is a far greater probability of having positive excess load under the DSR-R strategy as seen from the presence of boxes in all years post-2016. Indeed, in all years there is a higher likelihood of exceeding capacity with the DSR-R strategy, even though the empirical excess load never exceeds 1.82 MVA (and the 75% upper quartile never exceeds 0.3 MVA). There therefore exists a trade-off between cost and reliability for the two considered strategies, which a decision maker can now assess on a quantitative basis using the proposed RO model. The decision maker could assess whether each strategy meets a threshold in terms of acceptable risk, or, beyond this, may assign a corresponding economic value to the physical risk metrics, based on how the DNO might mitigate that risk operationally or, e.g., be penalized under their regulatory framework in the event that customers were off supply.

5.3. DSR pricing

Although the overall average NPC for the DSR-R strategy (strategy 2) is lower than for the traditional reinforcement R strategy (strategy 1), with respective mean costs of £647k against £981k, this difference clearly depends on input assumptions regarding the cost of DSR. Since DSR is an emerging technology, these costs may be uncertain. The decision maker can therefore assess the sensitivity of this conclusion to an estimated level of DSR costs by determining the maximum DSR payment that the DNO is willing to pay its DSR customers for the opportunity of using DSR as an alternative to asset reinforcement. In other words, one can assess how close the intended DSR payment price of £20k/MVA/year per customer from Table 3 is to the "break-even" value that the DNO is prepared to pay for avoiding a network

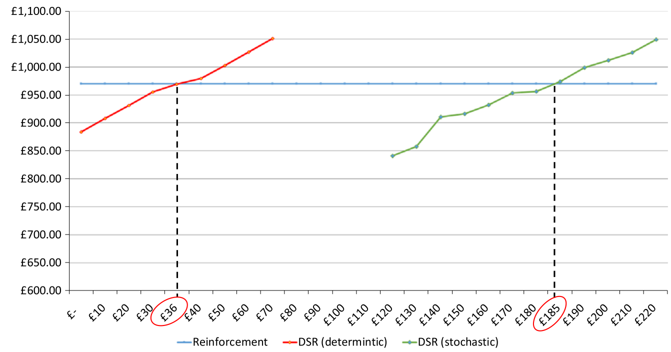

Fig. 10. Breakeven point for DSR payments – in scenario S2 (red) and Overall analysis with all scenarios (green). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

reinforcement, which is set by the average cost of the traditional reinforcement. This question may of course also be addressed through standard scenario analysis. Taking a deterministic approach, the probability weight of the 'best view' scenario S2 for example could be set to 100%, while S1 and S3 are set to 0%. Then, by varying the DSR payment amount from £20k/MVA/year per customer to £70k/MVA/year per customer for the DSR-R strategy, we see from Fig. 10 (red) that the breakeven DSR payment is £36k/MVA/year. This means that any DSR payment lower than £36k/MVA/year would result in the DSR-R strategy having lower average costs than the R strategy assuming the best view scenario materializes. However, for DSR payments greater than £36k/MVA/year, the R strategy would on average be the cheaper alternative under scenario S2 on the basis of such a deterministic analysis.

The flexibility provided by DSR has even greater value when there is uncertainty as shown in Fig. 10 (green). Our RO illustrative example above now considers all three scenarios, S1, S2 and S3, each with their associated probability of occurrence taken from Table 4 (layer 2) and with Monte Carlo simulations to represent small-scale uncertainty (layer 3). In this example, the "break-even" DSR payment amount can reach nearly £185k/MVA/year, over five times greater than the value calculated above using a standard scenario analysis of scenario S2. This means that taking account of uncertainty in future demand growth through the three scenarios results in a much greater value for the flexible DSR strategy. It hence allows the decision maker to assess the situation once uncertainty gives way to information and to react appropriately if demand grows more quickly or more slowly than originally anticipated. As discussed in Section 5.1, a significant part of this value arises due to the ability of DSR to avoid committing to a classical reinforcement, which subsequently becomes a stranded asset if peak demand then falls, as is the case in Scenario S3.

6. Conclusions and policy implications

This paper discusses the need to account appropriately for uncertainty in long-term decision making and the valuation of network investment plans, as accounting for uncertainty can significantly change the business case for flexible capacity-based services for postponing or even avoiding costly irreversible reinforcements. We have presented a case study illustrating that such flexible interventions can have significantly higher value when uncertainty is modeled, as compared to standard deterministic scenario analysis. We have also argued that inappropriate modeling of the information available to decision makers at the time of intervention (that is, assuming knowledge of the future) may conversely lead to the overestimation of the value of flexibility. We have therefore presented a practical RO tool that combines sophisticated RO analysis for valuing flexible investment strategies under uncertainty with the simplicity, practicality and transparency of a "playable" Excel-based spreadsheet tool that reflects the CBA tools currently used by DNOs to inform the Regulator on their investment plans. Because of this feature, we recommend network Regulators to implement this framework into their CBA tools. In particular, this tool builds on the standard existing approach of scenario analysis, incorporating this within a multi-layered model for uncertainty and flexibility. By modeling long-term and shorter-term uncertainties separately, we allow different investment strategies to be compared at the scenario level while accounting for uncertainty, and to then be combined to give an overall, probability-weighted analysis that is mathematically consistent. Costs and physical risks are calculated as *distributions* so that the decision maker may use a range of metrics based, for example, both on averages and on risk measures in selecting the preferred investment strategy. By directly comparing the value of DSR on a like-for-like basis with asset-based reinforcement strategies, a redistribution of the "profits" realized from significantly reducing network investment costs can now be assessed on a mathematically consistent and quantitative basis. As a key policy recommendation arising from our work, there is a need to change the current regulatory framework based on deterministic investment analysis and move on towards a probabilistic approach, such as the one presented in the paper. In fact, the modeling of uncertainty is the only way to explicitly quantify and acknowledge the value of flexible solutions such as DSR, and thus accrue all the relevant economic benefits mentioned above.

The breakeven analysis also provides a helpful indication of the sensitivity of these RO results to assumptions around DSR payments, which at present may be uncertain. Several conclusions regarding the value of DSR for planning can be drawn, together with corresponding policy implications. The provision of a flexible capacity-based DSR service may result in substantial cost savings through the deferral or avoidance of costly capital investments. Reducing capital costs in this way can translate into benefits for different actors in the value chain, and particularly for end customers to whom network costs are eventually passed on. As the first of its kind, our model allows an estimate of the economic value of DSR services, which could be used to inform DSR contractual arrangements based on the DSR payment price calculated by our model as an upper limit. If the contracted DSR price is equal to the upper limit on DSR price suggested by the model, then all of the cost savings of DSR versus traditional reinforcement are transferred as an economic benefit to the contracted DSR customers. If the contracted DSR price is lower, then the remaining economic benefit accrues to the network operator. In practice in a regulatory framework such as RIIO-ED1, any efficient cost saving is shared as a benefit to the DNO and a benefit to bill-paying customers. It is therefore in the interests of the DNO and its collective customers to contract for DSR at the minimum price possible.

Thirdly, the real options decision-support model has also been developed to rapidly highlight that differences exist in the economic perspective of the regulated DNO business and of customers in general. The DNO will use an appropriate discount rate for its business and be subject to financial incentives such as the Information Quality Incentive. Yet, from the perspective of bill-paying customers in general, there might be a lower discount rate, a cost to finance the DNO's investments, and the regulator might assign values to certain effects, which do not have a financial effect on the DNO.

The existence of these two policy perspectives (DNO vs. customer) then presents an interesting practical point that the strategy selection from our proposed model can help assess. When a strategy is favorable to the DNO but not to its customers in general, regulatory oversight of investment projects is needed to ensure that such a strategy is not followed. Conversely when a strategy is favorable to customers but would financially penalize the DNO business, this highlights situations in which the regulatory framework may need to be altered. Finally, when both DNO and customer perspectives lead to the same choice of strategy, this suggests that what is good for the DNO business is also good for its customers.

It is worth noting that our model provides metrics to enable decision-makers to easily and clearly understand the relative scale and likelihoods of both economic and physical risk effects arising from different investment strategies and different perspectives. However, as the proposed RO tool is intended for use in planning rather than for operational decision-making, the operational behavior by the DNO in response to contingencies such as ICT failures or contractual limits on the frequency of DSR requests, are not modeled here. Instead, we assume that the DNO is able to react to operational contingencies within the constraints of all operational safety regulations, within its capacity limits defined by the short-term emergency ratings of the equipment or in the extreme by deployment of temporary generation. The model can also help assess the amount of extra DSR to be contracted to guarantee that the minimum required level of DSR is available when needed, for instance due to uncertainty in customers not responding when called upon. In practice, the DNO may however consider a trade-off between reliability impacts when considering DSR, since a DSR strategy could decrease Customer Minutes Lost (CML) but increase Short Duration Interruptions (SDI). Nonetheless, the additional operational flexibility of the demand response solution proposed is expected to improve network reliability by (i) reducing restoration time decreasing CML to restore supply within three minutes once a contingency occurs; (ii) increasing SDI via strategic automation if the network in question is not currently automated (however these interruptions are likely to be less than three minutes and hence would not be regulated); (iii) redistributing power flows by potentially alleviating congestion in some lines and hence releasing some capacity by interconnecting adjacent radial feeders, and (iv) managing thermal or voltage constraints during emergency conditions.

However, the proposed tool gives a high level indication of the potential risk in the presence of DSR, which is indeed potentially suitable for the high-level decision making information that it aims to provide. For more specific information on the reliability consequences of a solution, more detailed reliability analysis should be performed, as thoroughly investigated within the C_2C project (Syrri and Mancarella, 2016) with results indicating that DSR solutions might be attractive also from a reliability point of view, as also found in (Kopsidas et al., 2016).

Improvements to the current model could include the DNO's regulatory financing costs, or the regulator's cost-reduction incentives relevant to losses, associated emissions, and reliability at the distribution level. Addressing such areas (which is work in progress) would take the model described in this paper closer to the cost treatment in Ofgem's CBA framework for RIIO-ED1, but once again this needs to be done under a proper uncertainty-aware framework. An appropriate analysis of these incentives and social costs is required to truly determine the consequences of different investment schemes – both to the distribution network operator company and to the Regulator (for a relevant policy-oriented, social perspective), so that flexible solutions can be adequately compared on par with traditional network reinforcements.

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References

Avner, B.-I., Strange, W., 1996. Investment Lags. Am. Econ. Rev. 86, 610–622. http://dx.doi.org/10.1126/science.151.3712.867-a.
Boyle, G., Guthrie, G., Meade, R., 2006. Real options and transmission investment: the New Zealand grid investment test.
Buzarquis, E., Blanco, G. a., Olsina, F., Garcés, F.F., 2011. Valuing investments in distribution networks with DG under uncertainty. In: Proceedings of the 2010 IEEE/PES Transmission and Distribution Conference and Exposition, Latin America, (T and d-LA) 2010, pp. 341–348, http://dx.doi.org/10.1109/TDC-LA.2010.5762904http://dx.doi.org/10.1109/TDC-LA.2010.5762904.
Carpaneto, E., Chicco, G., Mancarella, P., Russo, A., 2011a. Cogeneration planning under uncertainty. Part I: multiple time frame approach. Appl. Energy 88, 1059–1067. http://dx.doi.org/10.1016/j.apenergy.2010.10.014.
Carpaneto, E., Chicco, G., Mancarella, P., Russo, A., 2011b. Cogeneration planning under uncertainty. Part II: decision theory-based assessment of planning alternatives. Appl. Energy 88, 1075–1083. http://dx.doi.org/10.1016/j.apenergy.2010.08.019.
Cheng, C.-T., Lo, S.-L., Lin, T.T., 2011. Applying real options analysis to assess cleaner energy development strategies. Energy Policy 39, 5929–5938. http://dx.doi.org/10.1016/j.enpol.2011.06.048.
Davis, G.A., Owens, B., 2003. Optimizing the level of renewable electric R&D expenditures using real options analysis. Energy Policy 31, 1589–1608. http://dx.doi.org/10.1016/S0301-4215(02)00225-2.
Department of Energy and Climate Change (DECC), 2014. Delivering UK Energy Investment.
Electricity North West Ltd., 2014. Capacity to customers – key documents (WWW Document), ⟨http://www.enwl.co.uk/c2c/about-c2c/key-documents⟩.
Electricity North West Ltd., 2013. Accommodating demand side response in engineering, Recommendation P2/6 – Change Proposal.
Fuss, S., Szolgayova, J., Obersteiner, M., Gusti, M., 2008. Investment under market and climate policy uncertainty. Appl. Energy 85, 708–721. http://dx.doi.org/10.1016/j.apenergy.2008.01.005.
HMSO, 2000. Utilities Act, UK.
HMSO, 1989. Electricity ACT 1989, UK.
Kopsidas, K., Kapetanaki, A., Levi, V., Milanovic, J., 2016. Optimal demand response scheduling with real time thermal ratings of overhead lines for improved network reliability. IEEE Trans. Smart Grid . http://dx.doi.org/10.1109/TSG.2016.2542922, 1–1.
Marreco, J.D.M., Carpio, L.G.T., 2006. Flexibility valuation in the Brazilian power system: a real options approach. Energy Policy 34, 3749–3756. http://dx.doi.org/10.1016/j.enpol.2005.08.020.
Martínez Ceseña, E.A., Mancarella, P., 2014. Distribution network reinforcement planning considering demand response support. In: Proceedings of the 2014 Power Systems Computation Conference, IEEE, Wroclaw, Poland, pp. 1–7, http://dx.doi.org/10.1109/PSCC.2014.7038347.
Martinez-Ceseña, E.A., Turnham, V., Mancarella, P., 2016. Regulatory Capital and Social Trade-Offs in Planning of Smart Distribution Networks with Application to Demand Response Solutions, Electric Power Systems Research, accepted for publication.
National Grid, 2014. UK Future Energy Scenarios 2014.
Ofgem, 2015. Network Innovation (WWW Document), ⟨https://www.ofgem.gov.uk/network-regulation-riio-model/network-innovation⟩.
Ofgem, 2013. Strategy decision for the RIIO-ED1 electricity distribution price control: Outputs, incentives and innovation.
Ofgem, 2012. Real options and investment decision making, consultation. London, UK.
Onen, A., Cheng, D., Broadwater, R.P., Scirbona, C., Cocks, G., Hamilton, S., Wang, X., Roark, J., 2014. Economic evaluation of distribution system smart grid investments. Electr. Power Compon. Syst. 43, 224–233. http://dx.doi.org/10.1080/15325008.2014.975873.
Poudineh, R., Jamasb, T., 2014. Distributed generation, storage, demand response and energy efficiency as alternatives to grid capacity enhancement. Energy Policy 67, 222–231. http://dx.doi.org/10.1016/j.enpol.2013.11.073.
Schachter, J.A., Mancarella, P., 2016. A critical review of real options thinking for valuing investment flexibility in smart grids and low carbon energy systems. Renew. Sustain. Energy Rev. 56, 261–271. http://dx.doi.org/10.1016/j.rser.2015.11.071.
Schachter, J.A., Mancarella, P., 2015. Demand response contracts as real options: a probabilistic evaluation framework under short-term and long-term uncertainties. IEEE Trans. Smart Grid 7, 868–878. http://dx.doi.org/10.1109/TSG.2015.2405673.
Schofield, J., Stanojevic, V., Bilton, M., Strbac, G., Dragovic, J., 2013. Application of demand side response and energy storage to enhance the utilization of the existing distribution network capacity. In: Proceedings of the 22nd International Conference and Exhibition on Electricity Distribution (CIRED 2013),

Institution of Engineering and Technology, pp. 0852–0852, http://dx.doi.org/10.1049/cp.2013.0970.
Shaw, R., Attree, M., Jackson, T., 2010. Developing electricity distribution networks and their regulation to support sustainable energy. Energy Policy 38, 5927–5937. http://dx.doi.org/10.1016/j.enpol.2010.05.046.
Strbac, G., 2008. Demand side management: benefits and challenges. Energy Policy 36, 4419–4426. http://dx.doi.org/10.1016/j.enpol.2008.09.030.
Syrri, A.L., Mancarella, P., 2016. Reliability and risk assessment of post-contingency demand response in smart distribution networks. Sustain. Energy Grids Netw. 7, 1–12. http://dx.doi.org/10.1016/j.segan.2016.04.002.
Syrri, A.L., Martínez Ceseña, E.A., Mancarella, P., 2015. Contribution of microgrids to distribution network reliability. In: Proceedings of the 2015 IEEE Eindhoven PowerTech, IEEE, pp. 1–6, http://dx.doi.org/10.1109/PTC.2015.7232486.
Yang, M., Blyth, W., Bradley, R., Bunn, D., Clarke, C., Wilson, T., 2008. Evaluating the power investment options with uncertainty in climate policy. Energy Econ. 30, 1933–1950. http://dx.doi.org/10.1016/j.eneco.2007.06.004.